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A FEW-SHOT COPYRIGHT ATTRIBUTION FOR GAME IMAGE BASED ON META-LEARNING

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***ABSTRACT*:**

The rapid proliferation of digital game content has increased the need for reliable methods to identify the copyright ownership of game images, particularly in scenarios where only a limited number of labeled samples are available for each title, character, or visual asset. Conventional image classification approaches often require large-scale annotated datasets and show limited generalization across heterogeneous game domains, such as variations in genre, art style, rendering quality, and post-processing. To address these challenges, in this paper, we propose a few-shot copyright attribution framework for game images based on meta-learning. The proposed method is designed to learn transferable visual representations and fast adaptation strategies from episodic training tasks, enabling effective attribution of previously unseen or weakly represented game image classes. In addition, a cross-domain learning setting is considered to improve robustness against stylistic and content-level discrepancies among game datasets. The framework aims to distinguish copyright-related visual sources by capturing discriminative fine-grained patterns while maintaining generalization under data scarcity. In this paper, we have simulated a few-shot attribution scenario on a game image benchmark and evaluated the proposed framework using standard recognition and attribution measures. The results are expected to demonstrate that meta-learning provides a practical and scalable solution for copyright attribution in game images, offering strong potential for digital copyright protection, content monitoring, and forensic analysis in the gaming industry.

Keywords*: Meta-learning; Game image analysis; Copyright attribution; Few-shot learning*

INTRODUCTION

Digital games have become one of the most influential forms of digital media, generating large volumes of visual content such as characters, backgrounds, screenshots, items, promotional images, and user-generated derivatives. As these visual assets are increasingly circulated through social media, streaming platforms, game communities, and online marketplaces, identifying the copyright ownership of game images has become an important problem for intellectual property protection, digital asset monitoring, and forensic investigation.

Traditional image classification methods based on deep convolutional neural networks have achieved strong performance when large-scale labeled datasets are available. However, copyright attribution for game images differs from conventional object classification in several important aspects. First, copyrighted game assets may be represented by only a few labeled examples, particularly for newly released games, limited-edition characters, or proprietary visual elements. Second, game images show substantial cross-domain variation caused by genre, rendering engine, camera viewpoint, art style, post-processing, compression, and resolution. Third, copyright-related attribution requires the model to capture fine-grained and source-specific visual patterns rather than only semantic categories.

Few-shot learning and meta-learning provide a promising direction for this problem because they are designed to learn from episodic tasks and adapt rapidly to new classes with only a few support samples. Representative approaches such as Matching Networks [1], Prototypical Networks [2], Model-Agnostic Meta-Learning (MAML) [3], and Relation Networks [4] demonstrate that learning transferable representations or optimization strategies can improve recognition under limited data conditions. Nevertheless, their application to game image copyright attribution remains underexplored, especially in cross-domain settings where the source and target game datasets differ substantially in visual style. Recent cross-domain few-shot learning studies have shown that domain discrepancy can significantly affect the generalization ability of prototype-based recognition models [10].

This paper proposes a meta-learning-based framework for few-shot copyright attribution of game images. The framework is trained through episodic tasks that simulate N-way K-shot copyright attribution scenarios. Each task consists of a support set containing a small number of labeled game images and a query set requiring attribution to the correct copyright source. To improve generalization, cross-domain episodes are constructed across different game titles, genres, and visual asset categories. The proposed model learns a transferable embedding space in which images from the same copyright source are clustered while images from different sources are separated.

RELATED WORKS

Few-shot learning has been widely studied to address visual recognition problems where only a small number of labeled samples are available. Matching Networks introduced an episodic learning strategy that compares support and query samples through an attention-based mechanism, showing the possibility of learning new classes from limited examples [1]. Prototypical Networks further simplified few-shot classification by representing each class as the mean embedding of its support samples and classifying query samples based on their distance to class prototypes [2]. Relation Networks extended this metric-based direction by learning a trainable similarity function between support and query features rather than relying on a fixed distance metric [4]. These methods provide an important foundation for copyright attribution because a new game title, character, or visual asset may be represented by only a few reference images.

Meta-learning has also been actively investigated for rapid adaptation to unseen tasks. Model-Agnostic Meta-Learning (MAML) learns an initialization that can be quickly adapted to new classes with a small number of gradient updates [3]. Subsequent analyses of few-shot classification have shown that both representation quality and episodic training design are critical factors for stable few-shot performance [7]. Recent surveys further indicate that few-shot and meta-learning methods are effective for image understanding tasks under data-scarce conditions, while also emphasizing remaining challenges such as task diversity, overfitting, and generalization to unseen domains [9], [12].

Cross-domain few-shot learning is particularly relevant to game image copyright attribution because game images vary significantly in genre, art style, rendering engine, resolution, and post-processing. Zhou et al. showed that prototype-based methods can be effective in cross-domain few-shot recognition, but their performance is strongly affected by domain discrepancy [10]. Tian and Xie proposed adversarial meta-training to improve cross-domain robustness in few-shot learning scenarios [11]. A recent survey on cross-domain few-shot visual recognition also reports that domain shift remains a major limitation when models trained on one visual distribution are applied to another [13].

Image forensics and attribution studies provide another relevant research direction. Deepfake and image forgery detection research demonstrates that forensic models must capture subtle, fine-grained, and source-sensitive visual patterns rather than only high-level semantic categories [14]. Similarly, meta-learning has been applied to few-shot face forgery segmentation and classification, suggesting that few-shot learning can support forensic analysis when labeled samples are limited [15]. However, most existing studies focus on general object recognition, biometric recognition, or forgery detection, while few directly address copyright attribution for game images. Therefore, this paper proposes a meta-learning-based few-shot attribution framework tailored to game images, combining prototype-based recognition with cross-domain robustness for practical copyright monitoring.

PROPOSED SCHEME

All This paper proposes a few-shot copyright attribution framework for game images based on meta-learning. The main objective of the proposed scheme is to identify the copyright-related source of a query game image, such as its original game title, character, or visual asset class, using only a small number of labeled reference images. Unlike conventional supervised image classification methods that require large-scale annotated datasets, the proposed method is designed to learn transferable representations and rapid adaptation strategies through episodic training.

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Let the game image dataset be denoted as

$$\mathcal{D} = \{(x_i, y_i, d_i)\}_{i=1}^{M}, \tag{1}$$

where $x_i$represents a game image, $y_i$is its copyright attribution label, and $d_i$denotes its domain information, such as genre, art style, rendering type, or resolution. As shown in Eq. (1), each sample contains not only an image and its attribution label but also domain-related information used for cross-domain learning.

In the proposed framework, each training episode is formulated as an N-way K-shot task. An episode consists of a support set $\mathcal{S}$, which contains Klabeled samples for each of Ncopyright classes, and a query set $\mathcal{Q}$, which contains images to be attributed. The support and query sets are defined as

$$\mathcal{S} = \{(x_i^s, y_i^s)\}_{i=1}^{N\times K}, \tag{2}$$

$$\mathcal{Q} = \{(x_j^q, y_j^q)\}_{j=1}^{N\times Q}, \tag{3}$$

where Qdenotes the number of query samples per copyright class. Eqs. (2) and (3) describe the episodic structure used to simulate practical copyright monitoring scenarios in which only a few reference samples are available for newly released or weakly represented game assets.

The overall architecture of the proposed scheme is shown in Fig. 1. The framework consists of four major components: an episodic task sampler, a feature encoder, a meta-learning attribution head, and a cross-domain regularization module. First, the episodic task sampler constructs multiple N-way K-shot tasks from the game image dataset. The support set in Eq. (2) provides reference examples for each copyright class, while the query set in Eq. (3) is used to evaluate attribution performance during training. Second, the feature encoder maps both support and query images into a shared embedding space. The encoder can be implemented using a convolutional neural network or a transformer-based visual backbone, such as ResNet, EfficientNet, Vision Transformer, or Swin Transformer. The purpose of the encoder is to extract discriminative visual features that capture both global style information and fine-grained copyright-related patterns.

Our proposed scheme consists of a game image dataset module, an episodic task sampler, a feature encoder, a meta-learning attribution head, a cross-domain regularization module, a loss computation module, and a copyright attribution output module. During training, N-way K-shot episodes are generated to simulate low-data copyright attribution scenarios. The support and query images are embedded through a shared feature encoder, and the attribution head predicts the copyright source of query images based on prototype similarity.

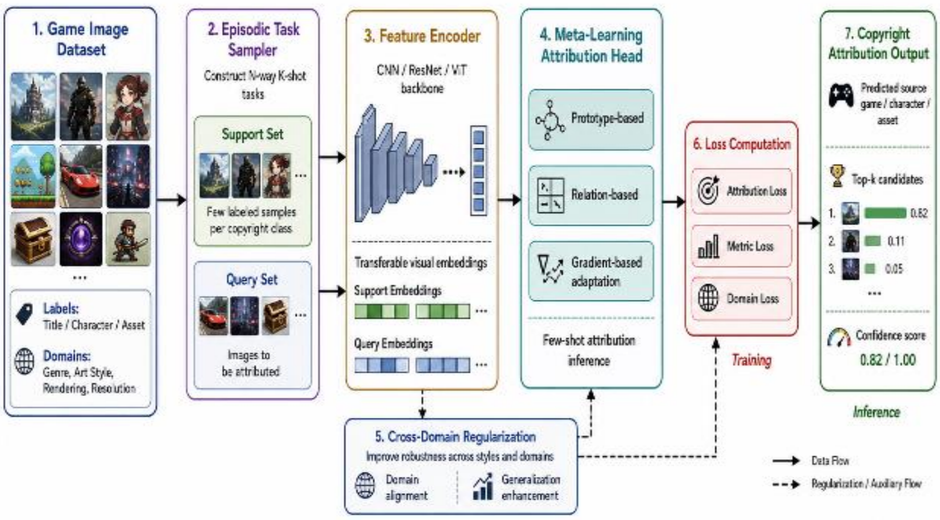

Fig. 1 Overall architecture of the proposed few-shot copyright attribution

Cross-domain regularization improves robustness against differences in genre, art style, rendering quality, and resolution.

Given an input image x, the feature encoder $g_\theta$produces an embedding vector as follows:

$$z = g_\theta(x), \tag{4}$$

where $z$denotes the latent representation of the input image. As shown in Eq. (4), all support and query images are transformed into the same embedding space by the shared encoder.
For each copyright class c, the proposed method computes a prototype vector by averaging the support embeddings belonging to that class:

$$p_c = \frac{1}{\mid \mathcal{S}_c \mid} \sum_{(x_i, y_i) \in \mathcal{S}_c} g_\theta\,(x_i), \tag{5}$$

where $\mathcal{S}_c$denotes the subset of support samples belonging to class c. Eq. (5) indicates that each copyright class is represented by a prototype vector computed from only a few labeled support samples.
For a query image x_q, its embedding is compared with each class prototype using a distance metric such as Euclidean distance or cosine distance. The attribution probability is then calculated by applying a softmax function over the negative distances:

$$P(y = c \mid x_q, \mathcal{S}) = \frac{\exp(-d(g_\theta(x_q), p_c))}{\sum_{c'} \exp(-d(g_\theta(x_q), p_{c'}))}. \tag{6}$$

As expressed in Eq. (6), a smaller distance between the query embedding and a class prototype produces a higher attribution probability. The query image is assigned to the copyright class with the highest probability:

$$\hat{y} = \arg\max_c P(y = c \mid x_q, \mathcal{S}). \tag{7}$$

Eq. (7) defines the final attribution decision. This prototype-based attribution strategy is suitable for few-shot copyright attribution because new game titles, characters, or assets can be registered using only a few labeled support images without retraining the entire classifier.

Game images often differ significantly in genre, visual style, rendering engine, resolution, and post-processing. Therefore, a model trained on one domain may not generalize well to another. The cross-domain regularization module encourages the feature encoder to learn domain-robust representations while preserving copyright-discriminative information.

The discrepancy between feature distributions from different domains can be reduced as follows:

$$\mathcal{L}_{domain} = \sum_{d_s \neq d_t} \begin{matrix} \parallel \mu\big(g_\theta(\mathcal{S}^{d_s})\big) \\ -\mu(g_\theta(\mathcal{Q}^{d_t})) \parallel_2 \end{matrix}^{2}, \tag{8}$$

where $d_s$and $d_t$denote different source and target domains, and $\mu(\cdot)$represents the mean feature embedding of a set. Eq. (8) encourages the model to reduce the distribution gap between support and query samples from different domains.

In addition, a metric loss is used to enhance intra-class compactness and inter-class separability:
The total training objective consists of attribution loss, metric loss, and domain regularization loss. The attribution loss is computed over the query set as

$$\mathcal{L}_{attr} = -\frac{1}{\mid \mathcal{Q} \mid} \sum_{(x_j^q, y_j^q) \in \mathcal{Q}} \log P(\,y_j^q \mid x_j^q, \mathcal{S}) \tag{9}$$

Eq. (9) optimizes the attribution probability of each query sample with respect to its ground-truth copyright label. The final objective function is defined as

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$$\mathcal{L}_{total} = \mathcal{L}_{attr} + \lambda_1\mathcal{L}_{metric} + \lambda_2\mathcal{L}_{domain}, \tag{10}$$

where $\lambda_1$and $\lambda_2$control the relative contributions of the metric loss and domain regularization loss, respectively. As shown in Eq. (10), the proposed method jointly optimizes attribution accuracy, feature discriminability, and cross-domain robustness.

During training, the model repeatedly samples few-shot episodes, extracts support and query embeddings using Eq. (4), computes class prototypes using Eq. (5), estimates attribution probabilities using Eq. (6), and updates the model parameters by minimizing Eq. (10). During inference, the trained model receives a small support set for candidate copyright classes and predicts the copyright source of a query image according to Eq. (7). In addition to the top-1 prediction, the model can provide top-k candidate sources with confidence scores, which is useful for practical copyright monitoring and human-in-the-loop forensic verification. Thus, the proposed scheme provides a scalable and flexible solution for game image copyright attribution under data-scarce and cross-domain conditions.

CONCLUSIONS

In this paper, we proposed a few-shot copyright attribution framework for game images based on meta-learning. The proposed scheme addresses the practical limitation of conventional supervised image classification methods, which generally require many labeled samples for each copyright class. In real-world game content monitoring scenarios, however, only a small number of reference images may be available for newly released games, limited-edition characters, rare visual assets, or proprietary game elements. To overcome this data scarcity problem, the proposed framework formulates game image copyright attribution as an N-way K-shot learning task and trains the model through episodic meta-learning.

Our proposed scheme consists of an episodic task sampler, a feature encoder, a meta-learning attribution head, and a cross-domain regularization module. The episodic task sampler constructs support and query sets to simulate few-shot attribution scenarios. The feature encoder extracts transferable visual embeddings from game images, while the prototype-based attribution head predicts the copyright source of a query image by comparing it with class prototypes generated from support samples. In addition, the cross-domain regularization module is designed to improve robustness against heterogeneous visual conditions, including differences in genre, art style, rendering engine, resolution, compression, and post-processing.

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